The Effect of Agricultural Growing Season Change on Market Prices in Africa

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http://dx.doi.org/10.5772/56459

1. Introduction

Local agricultural production is a key element of food security in many agricultural countries in Africa. Climate change and variability is likely to adversely affect these countries, particularly as they affect the ability of smallholder farmers to raise enough food to feed themselves. Seasonality influences farmers' decisions about when to sow and harvest, and ultimately the success or failure of their crops.

At a 2009 conference in the United Kingdom hosted by the Institute of Development Studies, Jennings and Magrath (2009) described farmer reports from East Asia, South Asia, Southern Africa, East Africa and Latin America. Farmers indicate significant changes in the timing of rainy seasons and the pattern of rains within seasons, including:

- More erratic rainfall, coming at unexpected times in and out of season;

- Extreme storms and unusually intense rainfall are punctuated by longer dry spells within the rainy season;

- Increasing uncertainty as to the start of rainy seasons in many areas;

- Short or transitional second rainy seasons are becoming stronger than normal or are disappearing altogether.

These farmer perceptions of change are striking in that they are geographically widespread and are remarkably consistent across diverse regions (Jennings and Magrath, 2009). The impact of these changes on farmers with small plots and few resources is large. Farming is becoming riskier because of heat stress, lack of water, pests and diseases that interact with ongoing pressures on natural resources. Lack of predictability in the start and length of the growing season affects the ability of farmers to invest in appropriate fertilizer levels or improved, high

yielding varieties. These changes occur at the same time as the demand for food is rising and is projected to continue to rise for the next fifty years (IAASTD, 2008).

Long-term data records derived from satellite remote sensing can be used to verify these reports, providing necessary analysis and documentation required to plan effective adaptation strategies. Remote sensing data can also provide some understanding of the spatial extent of these changes and whether they are likely to continue.

Given the agricultural nature of most economies on the African continent, agricultural production continues to be a critical determinant of both food security and economic growth (Funk and Brown, 2009). Crop phenological parameters, such as the start and end of the growing season, the total length of the growing season, and the rate of greening and senescence are important for planning crop management, crop diversification, and intensification.

The World Food Summit of 1996 defined food security as: "when all people at all times have access to sufficient, safe, nutritious food to maintain a healthy and active life". Food security roughly depends on three factors: 1) availability of food; 2) access to food and 3) appropriate use of food, as well as adequate water and sanitation. The first factor is dependent on growing conditions and weather and climate. In a previous paper we have investigated this factor by evaluating the effect of large scale climate oscillation on land surface phenology (Brown et al., 2010). We found that all areas in Africa are significantly affected by at least one type of large scale climate oscillations and concluded that these somewhat predictable oscillations could perhaps be used to forecast agricultural production. In addition, we have evaluated changes in agricultural land surface phenology over time (Brown et al., 2012). We found that land surface phenology models, which link large-scale vegetation indices with accumulated humidity, could successfully predict agricultural productivity in several countries around the world.

In this chapter we are interested in the effect of variability in peak timing of the growing season, or phenology, on the second factor of food security, food access. In this chapter we want to determine if there is a link between market prices and land surface phenology and to determine which markets are vulnerable to land surface phenology changes and variability and which market prices are not correlated.

2. Background

2.1. Vegetation seasonality and change

Early research on the impact of global climate change on the growing season in northern latitudes was based on satellite remote sensing observations of vegetation (Myneni et al., 1997, Nemani et al., 2003, Slayback et al., 2003). These direct observations of change in the onset of spring led to the development of phenological models using remote sensing information. Phenology is the study of the timing of recurring biological cycles and their connection to climate (Lieth, 1974). Phenology has the promise of capturing quantitatively the changes reported by farmers and providing evidence for its link to climate change. Land surface

phenology is the analysis of changes in the vegetated land surface as observed by satellite images (de Beurs and Henebry, 2004). Land surface phenology distinguishes itself from species centric phenology in that it focuses on the analysis of the land surface in mixed pixels. White et al. (2009) described the complexity of comparing ground observations of the start of season with satellite-derived estimates due to the difficulty in understanding the myriad definitions of season metrics.

Land surface phenology models rely on remote sensing information of vegetation, such as the dataset derived from the Advanced Very High Resolution Radiometer (AVHRR) (Tucker et al., 2005) and the newer MODIS sensors on Aqua and Terra. Vegetation and rainfall data can assess variables such as the start of season, growing season length and overall growing season productivity (Brown and De Beurs, 2008, Brown, 2008). These metrics are common inputs to crop models that estimate the impact of weather on yield (Verdin and Klaver, 2002). Land surface phenology metrics have a strong relationship with regional food production, particularly those with sufficiently long records to capture local variability (Funk and Budde, 2009, Vrieling et al., 2008).

2.2. Price seasonality

The integration of a market into the broader economy has been the objective of many development programs (Barrett, 2008), since the increased integration of food markets in developing countries is considered to be of vital importance for agricultural transformation and economic growth (Fafchamps, 1992). Market integration is also an important aspect of food security, since many sub-Saharan countries face food shortages as a result of crop failures caused by drought or other climatic hazards (Zant, 2013). Integrated markets offer the potential to reduce the impact of weather shocks by quickly moving food from surplus to deficit areas. Conversely, poorly integrated markets, such as those where inadequate trade infrastructure hinders market function, may result in food shortages (Zant, 2013). Poorly integrated markets are often isolated because of low participation in the market by farmers, resulting in 'thin' markets that have too little supply during times of high demand (before the harvest) and too much supply during times with low demand (after the harvest). Many households in developing countries seek to be as self-sufficient as possible in capital, labor and food to reduce exposure to variability in prices and extremely high transaction costs (Lutz et al., 1995), which are both a cause and a consequence of thinly traded, volatile markets. Thinly traded markets keep the difference between producer and consumer prices high, further reinforcing household incentives to minimize their reliance on markets (Tschirley and Weber, 1994, Kelly et al., 1996).

Seasonality in food prices, as measured by the ratio of post harvest to harvest prices, is high in markets that are poorly integrated and isolated. Seasonal price changes may reflect changes in production, particularly in good years when infrastructure and trade constraints reduce the ability of traders to move excess grain out of an area. Seasonal price spreads can be explained by storage losses, large postharvest grain sales, and lack of trader participation in isolated markets during average and good years (Alderman and Shively, 1996). Thus price seasonality is negatively related to production anomalies, where higher (lower) production will create

lower (higher) prices during the post harvest season because of the inability or unwillingness of households and traders to store grain.

Another source of seasonality in food prices in thin markets is the seasonality of transaction costs, as well as transportation costs. Little is known about the variability of transportation costs in each of the markets of this study, but rainfall and poor roads, increased demand for movement of goods and people during the rainy season, and the increased difficulty of distributing fuel and other necessities for transportation make it likely that transportation costs will be higher during the growing seasons (Alderman and Shively, 1996). Transaction costs are the costs incurred in making an economic exchange: determining the price and the demand for a good in a market, the cost of bargaining for a fair price, and the cost of policing and enforcement in the market (Asante et al., 1989, Fafchamps, 2004). All of these costs are also likely to be seasonal. These sources of non-food production variability in the seasonality of food prices can also be estimated with remote sensing data.

3. Data

3.1. MODIS data

MODIS Nadir BRDF-Adjusted Reflectance data (Schaaf et al., 2002) at 0.05° spatial resolution with temporal resolution of 16 days (MCD43C4) and temporal coverage from 2001 through 2011 were employed to derive the Normalized Difference Vegetation Index as:

$$NDVI = (NIR - RED) / (NIR + RED) \tag{1}$$

Where, NIR is the near infrared reflectance of MODIS band 2 (841-876 nm) and RED is MODIS band 1 (620-670 nm). NDVI is an often used vegetation index (Brown et al., 2006, Karnieli et al., 2010) which exploits the significant difference between NIR and Red reflectance for living vegetation. Healthy living vegetation strongly absorbs red reflectance and strongly reflects NIR.

3.2. MOD 16 evapotranspiration data

We used the MOD16 global evapotranspiration product at 0.05° spatial resolution and 16-day temporal resolution. The ET algorithm is based on the Penman-Monteith equation (Monteith, 1965, Mu et al., 2011). We accumulated the global evapotranspiration starting in January and July to account for the different growing seasons in the Northern and Southern Hemisphere.

3.3. Market data

The data used in this paper is from a continuously updated price database comprised of food prices from 232 markets in 39 countries, collected by the FAO and the US Agency for International Development's Famine Early Warning Systems Network (FEWS NET). The data is

available from the FAO at the Global Information and Early Warning System (GIEWS) website: http://www.fao.org/giews/pricetool/. We selected all the available markets that are located on the African continent. We have a total of 933 time series with market price information for 51 different products ranging from fuel to cattle to grain crops. The most common commodities were maize (137 price series), sorghum (118 price series), rice (102 price series), millet (56 price series), beans (43 price series) and cowpea (40 price series).The monthly time series differ in length with some starting as early as 1997 while others started in 2009. For time series with long data, only the period from 2000 was analyzed, and for those beginning after 2000, we report only the stations with at least four years of continuous data. We created a 0.5° buffer around the markets and determined the percentage of cropland within these buffers.

4. Methods

4.1. Land surface phenology metrics

To extract the peak height in NDVI and the peak timing based on accumulated evapotranspiration, we fit quadratic models with accumulated evapotranspiration based on MOD16 as the independent variable and NDVI as the dependent variable (Figure 1). We have used these models before based on Accumulated Growing Degree Days (AGDD) in other parts of the world (de Beurs and Henebry, 2008a,b, 2010). We have demonstrated recently that models based on moisture variables resulted in higher R^2 values in large areas around the world including Africa (Brown et al., 2012). In that paper we based our analysis on AVHRR data and we extend that work here with MODIS data. We fit the model two times for each pixel and year, once with data beginning in January and ending in December, and once with data beginning in July and ending in June. Figure 1 provides an example of the quadratic models for a market in Niger. For each 0.05° we calculate the NDVI peak height and the amount of accumulated evapotranspiration necessary to reach this peak NDVI. We also derive the day of the year for which the peak NDVI is reached.

4.2. Market analysis

Market prices are provided in monthly time series. Most market price series show a steady increase between 2000 and 2011 as a result of inflation and changes in world market prices. In this study we are not interested in the trend in these time series but rather in its seasonality. We calculate in which month, on average, the maximum price occurred, and we calculate the seasonal price spread. In addition, we calculate the difference between the maximum market price in each year and the minimum market price in the preceding eight months (Figure 2).

We apply Spearman's rank correlation to calculate the correlation between these price differences and the peak height based on our land surface phenology metrics (Figure 3).
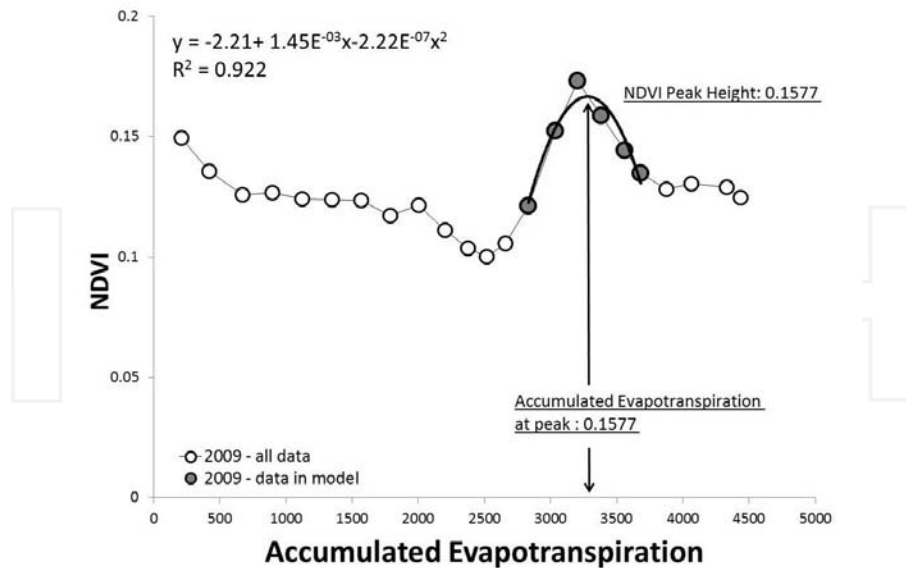
Figure 1. Example of a quadratic model fit for a station as far north as Ouallam, Niger. The example is created based on data from 2009. The NDVI peak height and the accumulated evapotranspiration at peak are calculated based on the quadratic regression model.

5. Results

5.1 Seasonal timing of vegetation and prices

The timing of the annual price maximum reveals a basic north-south pattern similar to the timing of the peak of the growing season observed by the land surface phenology models (Figure 4). The highest prices in West Africa occur in June and July in the far west, and in August and September in the central region. In East Africa the peak times occur in October and November, although a fair bit of variability can be observed. Southeastern Africa reveals highest prices in the months December through March. Figure 4 reveals that a great number of price time series peak around or slightly before the time that the vegetation as observed by satellite data peaks. There are a fair number of outliers, which are likely the result of non-environmental factors weighing more strongly on the price time series.

Figure 5 shows the seasonal price spread. The spread is highest for southeastern Africa and lowest for Western Africa. A low seasonal price spread indicates a certain amount of predict-ability about when prices may peak during the year.

Figure 2. Example of a price time series of millet prices in Ouallam, Niger. For each year we determine the highest price (in grey dots). We also determine the difference between the highest price and the lowest price in the preceding 8-month period (shown in black triangles). Based on the highest prices we calculate in which month on average the highest price is found.

5.2. Correlation between vegetation peak height and price increases

We found that the significance of the correlation between price increases and NDVI peaks in the surrounding areas differed strongly by product. For example, we found that only 13% of the rice price series correlated significantly ($p<0.1$) with NDVI peaks, while 35% of the cowpea price time series correlated strongly with NDVI peaks in the surroundings (Table 1).

Crop	Number of markets	% of sign. correlations
Cowpea	26	35%
Sorghum	76	32%
Beans	30	23%
Millet	41	22%
Maize	89	22%
Rice	46	13%

Table 1. Percent of significant correlation between market price increases and NDVI at peak by crop type.

Table 2 provides the 10 countries for which we have the largest number of market price series. We found a fair bit of variability in the number of significant correlations by country. For
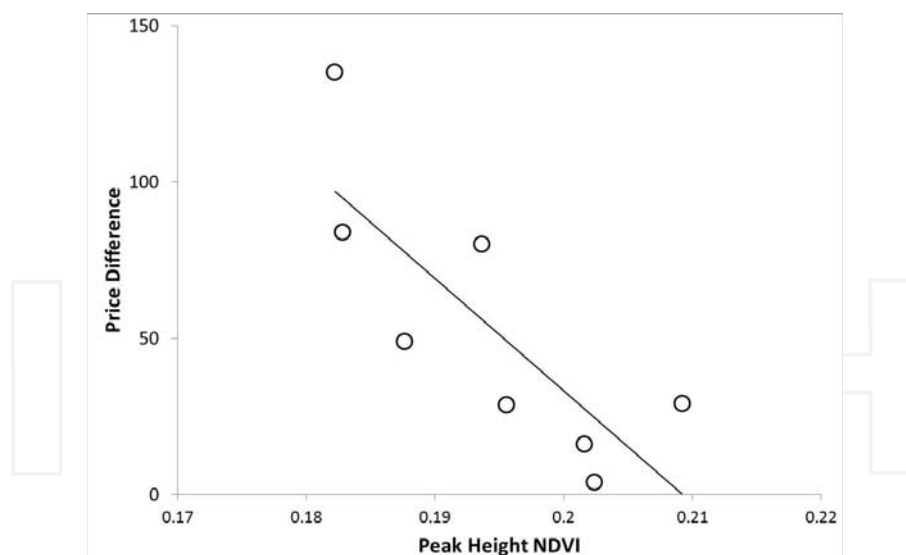
Figure 3. Example of correlation between the peak height of NDVI (Figure 1) and the price difference calculated based on market prices (Figure 2) for Ouallam, Niger. Each dot indicates a peak height x price difference combination for one year. We are showing the years 2004 – 2011. The final reported rank correlation for this area was -0.56, with a p-value of 0.037.

example, Nigeria, Somalia and Niger all revealed significant correlations between price increases and NDVI peak height for a large percentage of their markets (50%, 42% and 33%, respectively), while only 11% of the markets in Burundi revealed significant correlations.

Country	Number of markets	% of sign. correlations
Nigeria	22	50%
Somalia	45	42%
Niger	24	33%
Kenya	18	22%
Tanzania	28	18%
Mali	22	18%
Mozambique	22	14%
Burkina Faso	15	13%
Uganda	17	12%
Burundi	18	11%

Table 2. Percent of significant correlation between market price increases and NDVI at peak by country.
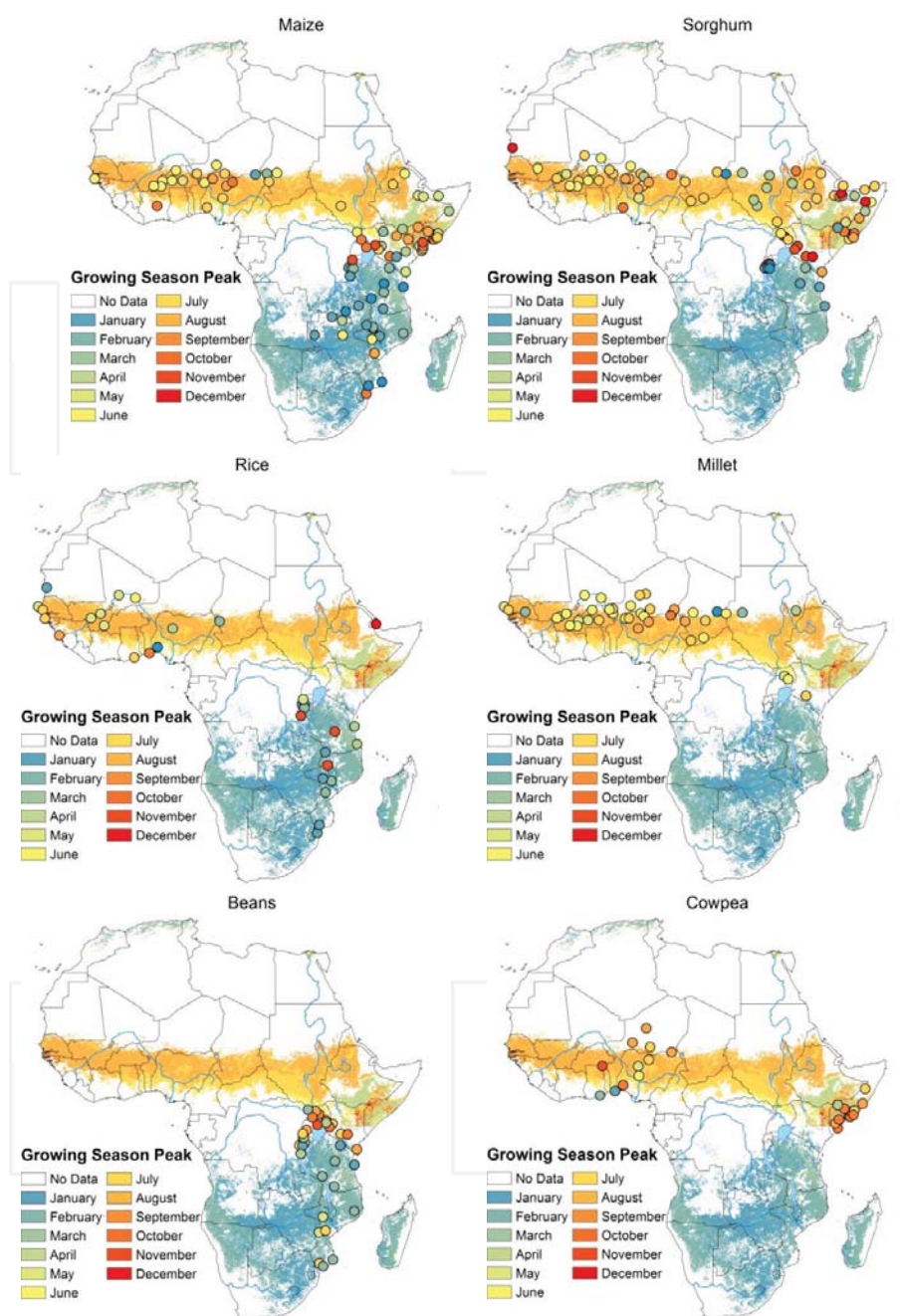
Figure 4. Mean month with the highest prices corresponds reasonably well with the peak timing based on NDVI.
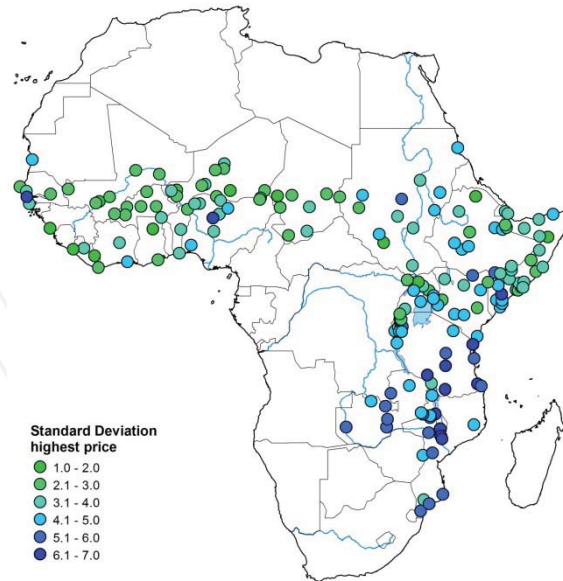
Figure 5. High seasonal price spread indicates more variability in the timing of the price peaks. Low price spread indicates that the annual maximum prices are found approximately in the same month every year.

5.3. Correlation between the amount of accumulated evapotranspiration at peak vegetation and prices

When we calculated the correlation between the peak timing in accumulated evapotranspiration and actual price values at their annual peak, we found a high number of markets with significant correlation, especially for millet. Beans revealed the lowest number of markets with significant correlation (16%). When we investigate the correlations by country, we find the largest number of significant correlations in Mali (Table 4), where 48% of the market price series correlate significantly with the peak timing in evapotranspiration units. Kenya and Burkina Faso also show a large number of significant correlations (45% and 40%). The lowest number of significant correlations was found in Tanzania, where only 15% of market price series correlated significantly with the amount of accumulated evapotranspiration at peak timing.

6. Discussion

In Sub-Saharan Africa, rice is the dominant commodity that appears to reflect changes in world prices (Kelly et al., 2008). Consequently, it is profitable to import rice, while arbitrage opportunities for grain trade are significantly lower. Further, several countries (many in West Africa)

consume rice, but need to import rice to meet domestic consumption needs. Thus, our lack of correlation between rice price series and NDVI in the surrounding regions appears reasonable (Table 1 and 3). Millet is one of the products that can be grown in semi-arid zones and is most widely available (Brown, 2008). The ability of millet to grow in semi-arid zones likely results in the higher number of markets that reveal significant correlations between prices and evapotranspiration (Table 3).

Crop	Number of markets	% of sign. correlations
Millet	46	35%
Sorghum	84	32%
Maize	112	31%
Rice	54	30%
Cowpea	26	23%
Beans	36	16%

Table 3. Percent of significant correlation between market prices and amount of evapotranspiration at peak by crop type.

Eight of the countries investigated are classified as having low food security; Nigeria and Burkina Faso are classified as middle food security (Yu et al., 2010). All have unfavorable climates for agriculture, except for Uganda and Burundi, which also show the lowest amount of correlation between NDVI peak height and price increases (Table 2). It appears that price changes in these two countries are less affected by weather conditions. More than 70% of cereal needs are generally met through domestic production in Mali, Burkina Faso and Niger (Kelly et al., 2008). As a result, food prices tend to rise as a result of production short falls. We found that prices in these countries revealed very high correlation with peak height NDVI (Niger, Table 2) and amount of accumulated evapotranspiration at peak (Mali and Burkina Faso, Table 4).

Country	Number of Markets	% of sign. correlations
Mali	23	48%
Kenya	22	45%
Burkina Faso	15	40%
Nigeria	25	36%
Uganda	22	32%
Somalia	49	29%
Niger	24	25%
Mozambique	23	22%
Burundi	22	18%
Tanzania	34	15%

Table 4. Percent of significant correlation between market prices and amount of evapotranspiration at peak by country.

7. Conclusions

Preliminary conclusion based on this analysis is that we can get a better understanding of where satellite data could aid in the prediction of local market prices. For example, prices may be driven by different factors in Uganda and Burundi than in Niger and Nigeria. If we combine our knowledge of the effect of large scale climate oscillations on the land surface phenology (Brown et al., 2010) with the links between price time series and land surface phenology, we may be able to get an understanding of where we could predict local prices. Satellite data may be most effective in predicting local prices in poorly integrated markets. Poorly integrated markets are often 'thin' markets that have too little supply during times of high demand, such as right before harvest, resulting in food shortages. Seasonal price changes may reflect changes in production; in good years infrastructure and trade contraints reduce the ability of traders to move excess grain out of the area, and in poor years food is not moved into the area.

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